THE EFFECT OF CREDIT RATINGS ON EMERGING MARKET VOLATILITY

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ABSTRACT

Through the use of an EGARCH model and a fixed effects panel regression, the reaction of emerging market stock and bond volatility to sovereign credit ratings changes is examined. The daily data covers the period of 1990 to 2016 and emerging market crises, such as the 1994 Mexican peso crisis, 1997 Asian financial crises and the global 2008 financial crises. The estimations provide evidence of an asymmetric effect of rating changes on stock volatilities, whereby downgrades have a significant impact, while upgrades have no such effect. For bonds the effect is ambiguous with both upgrades and downgrades having an effect. Downgrades are found to increase both stock and bond market volatility. On aggregate, contagion effects amongst stocks are found for emerging markets, as well as for the continents of Asia and Europe. No such evidence is found for bonds.

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1 CHAPTER 1: INTRODUCTION

1.1 Background

Credit ratings, as evidenced in the past decade, are coming into the spotlight as emerging markets are assigned a sovereign credit rating for the first time. As such, investors are looking to emerging markets as new investment horizons (Kraussl, 2005). The reason for this is that credit ratings give an indication of the willingness of sovereign states to meet their debt obligations. This is done by assessing the risk inherent in emerging markets, thus allowing investors to make international investment decisions (Amstad & Packer, 2015). In making these decisions volatility in emerging markets is thus pivotal to the investor's decision making process. This study assesses the volatility of stock and bond markets of emerging markets and how they are affected by ratings upgrades and downgrades. It also looks at the asymmetries inherent in negative and positive return shocks on future returns. The study thus continues to delve into the contagion effects of ratings changes and assesses if emerging markets display interdependence in their second moments.

After the 2008–2009 financial crisis, the importance of having accurate credit ratings became instrumental to navigating the financial minefield of sub-prime debt. Inaccurate ratings have been argued to have exacerbated the financial crisis, and have been found to have a greater impact on bond and stock markets, post 2008 (Kang & Min, 2016). Volatility has had a marked increase in several European Union (E.U.) countries after the financial crises (Afonso, Gomes, & Taamouti, 2014). These events can be associated with increased indebtedness of European states, resulting in exacerbated financial instability and degraded investor confidence, both ending with funding constraints to these nations. Despite these caveats, the consistent increase in debt issuers across the world has increased the demand for ratings. As such, rating agencies control the gateway to capital markets for bond issuers and debt market participants (Williams, Alsakka, & Gwilym, 2013).

Since emerging markets are among the largest high-yield borrowers in the world, ratings agencies are of vital importance to them (Ismailescu & Kazemi, 2010). As such, some of the largest emerging markets - BRICS (Brazil, Russia, India, China and South Africa) have decided, amongst themselves, to set up a ratings agency, catering specifically to emerging markets, with future intentions of rivalling the three main ratings agencies - Standard and Poor's (S&P), Moody's and Fitch (Beniwal, 2016). This agency will seek to eliminate the moral hazard problem inherent in American rating agencies' revenue model. Companies are currently required to pay the very same ratings agencies that assign them with a rating, therefore imposing an ethical dilemma. FitzGerald (2009) points out that even if sovereign states do not intend issuing cross border debt in the immediate future, they still seek out credit ratings. This is due to benefits such as fostering Foreign Direct Investment (FDI), promotion of more vibrant local capital markets, and increased public sector financial transparency.

The credit ratings literature is extensive, with the majority of papers cited examining macroeconomic drivers of ratings changes (Cantor & Pacher, 1996; Afonso, 2003; Kraussl, 2005; Erdem & Varli, 2010; Montes, Oliveira, & Mendonça, 2016; Borenszstein, Valenzuela, & Cowan, 2006; Williams et al, 2013; Hammoudeh, Sari, Uzunkaya & Liu, 2012). Other cited literature has delved into the transmission of ratings changes, examining whether they lead to an overall positive or negative effect on markets. Authors such as Amstad and Packer (2015) and Williams et al. (2013) have argued the importance of credit ratings for investors in making asset allocation decisions. Contrastingly, Li, Joen, Cho and Chiang (2007), Mora (2006) and Kraussl (2005) argue that ratings agencies are slow to respond to economic activity, which exacerbates and prolongs financial market upswings and downswings

The purpose of this study is to examine emerging market stock and bond volatility for the period of 1990 to 2016, and to dissect the different facets of credit rating changes' effects on stock and bond market volatility for these markets. Over the period of 1990 to 2016, this study covers emerging market crises, such as the 1994 Mexican peso crises, 1997 Asian financial crises and the global 2008 financial crisis. This study complements previous studies covering the effects of ratings upgrades and downgrades on stock and bond market volatility. These include studies such as Christiansen's (2007) study of contagion and volatility spill-overs amongst the United States (U.S.) and European bond markets; Engle, Gallo, and Velucci's (2012) study of volatility spill-overs in East Asian financial markets, as well as Afonso et al.'s (2014) study of volatility spill-overs resulting from credit rating changes amongst EU nations.

Primarily, it serves to provide a unified framework that combines sovereign rating and contagion literature, creating a link between rating changes and stock and bond second moments. Other papers have not linked these concepts for emerging markets as a whole. It also eliminates the bias that is typically associated with only making use of the three mainstream rating agencies, by making use of a total of nine ratings agencies. This provides a unique emerging market view of the effect of ratings changes on bond and stock second moments.

The importance of this study is three-fold in understanding the impact of sovereign rating changes on financial markets. Firstly, it adds to the theoretical understanding of the price discovery process by directly evaluating the variables that are pertinent to financial markets in the pricing of assets - being returns and volatility.

Secondly, it provides valuable information for international investors and managers of international portfolios. Managers and investors are faced with a wave of information relating to the risk of investing in foreign nations, often turning to sovereign credit ratings as a country risk indicator. Engle et al. (2012) and Gallo and Velucchi (2012) note that when investors are faced with increased volatility in their country's stock markets, they naturally reduce their positions due to the extra risk. French and Porterba (1991) analyse the benefits to investors of international diversification amongst advanced economies' stock markets. They found advanced economies' stock markets are highly correlated, and thus cross border risk reduction was less effective relative to emerging markets.

Thirdly, a comprehensive understanding of the effects of ratings changes on financial markets will improve financial market policy. If ratings do in fact have an effect on stocks and bonds, then they can exacerbate and prolong financial crises. Policies should therefore address this possibility, additionally factoring in potential contagion from other financial market downgrades and upgrades. Furthermore, financial and economic crises tend to be regional in nature, as was evident during the recent recessions, such as the European debt crisis, the Asian financial crisis and the Argentine debt crisis (Kaminsky et al, 2002). Thus, an understanding of spill-overs across emerging markets and within regions can be used not only reactively but proactively too, possibly smoothing out financial crises or business cycle upswings and/or downswings.

In hypothesis, a nation that is risky is expected to be more volatile. The lower a nation's credit rating, the more volatility will be inherent in the sovereign nation's bond and stock markets. Heinke (2006) finds evidence of lower grade bonds being more volatile, while Jaramillo and Tejada (2011) find evidence of lower grade bonds having larger spreads. It is also hypothesised that negative rating changes will only have an effect on the second moments of bonds and stocks, while positive ratings changes will have no effect. This is expected as previous research finds that positive rating changes have negligible effects on returns, while negative ratings changes have statistically significant effects on stock and bond returns. These significant effects can be expected to perpetuate into the second moments of the stocks and bonds. With regard to contagion, it is hypothesised that nations that are geographically close can be expected to have significant volatility spill-over effects on one another.

1.2 Research aim and objectives

This study seeks to provide a more detailed understanding of the effects of credit ratings on emerging markets. Moreover, this research assists investors in their international investment decisions. Furthermore, it assists policy makers in protecting financial markets from prolonged financial crises. This is done through the following three main aims.

(i) To analyse whether countries with higher credit ratings exhibit less volatility than lower rated countries

(ii) To examine the differences in the effects of positive versus negative announcements on volatility for emerging markets; and

(iii) To assess whether volatility in non-event countries react to rating changes of other event countries (contagion), and whether there are asymmetries in the transmission of these spill-over effects.

1.3 Research structure

The order followed by this research is as followed:

Firstly, it focuses on a literature review that covers important studies vital to the understanding of credit ratings and their effects. It covers the drivers of credit ratings, transmission mechanisms, ratings changes effects on bonds and stocks, the bias towards downgrades, as well as an analysis of bond and stock volatility and contagion effects.

Secondly, the methodology is then detailed, and the EGARCH and the fixed effects panel approach are explained at length.

Thirdly, a number of findings are reported that add fresh insights to the literature. In addition, the volatility of stocks is shown to increase as the credit rating of emerging markets deteriorates, but there is no clear visual pattern present for bonds.

Fourthly, downgrades are shown to have a statistically significant effect on the second moments of stock and bond returns while upgrades are shown to have a negligible effect.

Lastly, on aggregate, contagion effects amongst stocks are found for emerging markets, as well as for the continents of Asia and Europe. No such evidence is found for bonds.

2 CHAPTER 2: LITERATURE REVIEW

2.1 Drivers of ratings changes

It is widely known that rating agencies do not explicitly reveal their methods. Due to this opaque approach, the drivers of rating changes are not strictly known. An early paper by Cantor and Pacher (1996) identified what they thought were the seven most important macroeconomic variables to drive ratings changes. The study was comprehensive, covering 49 developed and developing nations, using a cross sectional regression. They found that for a $1000 rise in per capita income, ratings for S&P increases by 1.5 grades on average. In addition, Cantor and Pacher (1996) also found that developing nations tend to be three grades lower on average, and having a history of default leads to a rating two grades lower than a nation that maintained its debt obligations.

These results were further reinforced by Afonso (2003), where he identified the six main determinants of credit ratings changes. These include Gross Domestic Product (GDP) per capita, external debt-to-exports ratio, level of economic development, default history, the real growth rate, and the inflation rate. Similar drivers were evidenced by Erdem and Varli (2014). Using quarterly data from 2002 to 2011 for emerging markets, their results indicate that the variables of Budget Balance/GDP, GDP per capita, Governance Indicators and Reserves/GDP have a significant effect on credit ratings independent of rating scale. In their ordered response analysis, all significant variables in the linear models plus External Debt/Export variable appear to be significant.

Afonso's (2003) study examined 81 developing and developed nations, finding that GDP per capita emerges as virtually the sole relevant economic driver for developed countries, while external debt is important for developing countries.

Prior to the 1990's, few papers focused exclusively on rating changes in emerging markets, but that is fast changing. From 1993 to 2000, Moody's saw a more than five-fold growth in the number of emerging market sovereigns that received a credit rating on their long term foreign currency debt issues. The figures indicate that in 1993, Moody's assessed only 12 emerging market economies. However, the number of rated governments accelerated rapidly in the mid-1990s, as several governments, particularly transition economies and countries in the Middle East, sought access to international bond markets (Kraussl, 2005).

In response to this growth in rated emerging markets, Montes et al. (2016) conducted a panel data approach for the 1994 to 2013 period. They found that GDP Growth, Per Capita GDP, Inflation, foreign reserves, government budget balance and external debt were all significant macroeconomic drivers of rating changes. They also found that the adoption of inflation targeting, financial openness, democracy, law and order, and less corruption are important drivers to improve the sovereign rating of a developing nation. The study also sought to highlight the importance of the adoption of inflation targeting, finding that inflation targeting nations generally had better ratings than non-inflation targeting countries.

Williams et al. (2013) adds to the dynamic of Montes et al.'s (2016) paper. In their findings, the higher the score of economic freedom, financial freedom, government spending, investment freedom and business freedom, the less likely banks are to be upgraded, following recent sovereign rating upgrades. The results show that the lower the economic, financial, investment and business freedom of a nation, the more likely locally owned banks are to be upgraded following a sovereign upgrade and vice versa for downgrades. A study that focused on separate economic, political and financial risk ratings of each nation gives clarity as to the long run effects of risk changes on stock exchanges. Using the BRICS nations over the 1992 to 2011 period, Hammoudeh et al. (2012) found that debt servicing, international liquidity, Balance of Payments (BOP) as a percentage of GDP and exchange rate stability emerge as important drivers of risk to stock markets.

As can be seen from the majority of studies, there is an overlap of important macroeconomic drivers of rating changes. GDP, however, emerges as the most prominent and significant driver.

2.2 Transmission of ratings changes

GDP depends on private consumption, government spending, exports, imports and finally, private investment (Blanchard, 2011). Ratings changes affect sovereign nations through transmission mechanisms, one being private investment or the investment channel (Chen, Chen, Chang, & Yang, 2013). Chen et al. (2013) explain that credit ratings affect physical investment through the cost of capital to firms. Uncertainty in financial markets can cause a flight–to-quality effect where investors prefer to move their funds to safer assets. The basic premise is that if a country suffers from a rating downgrade it becomes riskier, thus pushing interest rates up. Investment projects that were previously viable with a positive net present value (NPV) become unviable with negative NPV's. As a result, investment decreases, reducing GDP.

Chen et al. (2013) confirmed that following a ratings upgrade/downgrade, there is a significant increase/decrease in private investment growth in a nation. This was found by making use of a dynamic panel data approach for 48 nations, however, the effects were found to be temporary - lasting for one year after the downgrade/upgrade. On average, private investment growth was shown to be 3.2%, but after the downgrade, it dropped to -11.5% and -10.1% in the subsequent years. The hypothesised reason for the temporary effects: when a downgrade occurs, it increases a country's risk premium. Thus, investors stall investment until new information arises, in turn, causing the initial drop in private investment, and then returning to normal.

By examining data for the cost of capital, Chen et al. (2013) solidified this empirical link between ratings changes and their effect on private investment. This was done by proving an empirical negative correlation between the cost of capital and private investment. A significant effect of ratings changes on the cost of capital and hence, on private investment, was found.

In addition to transmission mechanisms such as the investment channel, ratings agencies' policies have transmission effects. A policy shared by most ratings agencies is that the rating of a private company cannot be higher than that of the sovereign nation in which it resides. As Moody's (2015) explain, credit ceilings show the maximum rating for a debt issuer where that issuer originated its cash flows in a particular country. This policy is termed the 'Sovereign Credit Ceiling' and has detrimental effects for private companies due to rating changes. In essence, if the sovereign nation is downgraded, then so are private companies and with a lower rating, they will have less access to financing.

The motivation for the rule was that government holds the first claim on any available foreign exchange reserves, and thus controls the domestic company's ability to get hold of foreign currency during a crisis (Kraussl, 2005). In order to investigate the effects of 'Sovereign Credit Ceilings' Almedia, Cunha, Ferreira, and Restrepo (2016) separated firms into bounded firms and non-bounded firms. Bonded firms had a company rating equal to the sovereign rating, while non-bounded firms had a rating below the sovereign rating. They found that bounded firms were significantly more likely to be downgraded after a sovereign rating downgrade than a non-bounded firm. The consequences of this were found to be that bounded firms cut investment, reduce net debt issuance and increase equity issuance more than non-bounded firms, following a downgrade. This results in a significantly greater increase in their cost of capital compared to non-bounded firms (Almedia et al., 2016).

When taking a more specific look at the effects of the sovereign ceiling rule, the banking sector makes for a prime example. Williams et al. (2013) found that a bank is 63.2% more likely to be upgraded by one notch on the ratings scale if the sovereign nation had a one notch upgrade. If the sovereign nation is upgraded by two notches then the probability of the bank being upgraded is even higher, sitting at 87.1%. With regards to downgrades, a bank is 26% more likely to be downgraded by one notch on the ratings scale following a one notch sovereign downgrade, and 62.2% more likely to be downgraded by two or more notches following a two or more notch sovereign downgrade (Williams et al., 2012).

The sovereign credit ceiling as a policy has however, slowly started to fade away. In April 1997, S&P relaxed its sovereign ceiling rule for three dollarised economies - Argentina, Panama, and Uruguay which began a cascading effect of revoking the policy across ratings agencies (Almedia et al., 2016). Even though the policy has largely been revoked, its effect has remained. Borensztein et al. (2013) conclude that the 'Sovereign credit ceiling' policy tends to remain in effect, particularly in countries where capital account restrictions are still in place, but is not statistically significant for countries that are financially liberalised. This is however, a critical issue for well managed and reliable private firms in emerging markets, as sovereign ratings in emerging markets tend to be on average lower than that of developed nations.

Besides the sovereign ceiling rule, a grade of a bond can determine whether it is allowed to be traded as per regulation. Kraussl (2005) notes that for institutional investors, this is critical as they operate within the bounds of their trading parameters. For example, an investor that manages an investment grade bond portfolio can be restricted from holding speculative grade bonds. This transmits directly to the demand for bonds, if a sovereign rating upgrade occurs from speculative to investment grade, it can open a nation up to portfolio diversification from foreign investors, thus increasing the demand for bonds, and stabilising bond demand simultaneously. The opposite is true where a nation is downgraded, it can reduce and destabilise the demand for bonds.

As to the effectiveness of the transmission mechanisms, this depends on the Efficient Market Hypothesis (EMH). The EMH predicts that if ratings agencies use publicly traded information to create sovereign ratings, then stock and bond prices will not adjust in reaction to rating announcements. This is because the market would have already taken the rating changes into account and adjusted accordingly (Brooks et al., 2002). Ding, Clive, Granger, and Engle (1993) analysed daily returns on the S&P 500 stock index. In doing so, they found that most stock series have a positive first order correlation, suggesting that stocks do, in fact, have a small amount of memory incorporated into their pricing. Even though this effect is found to be short lived, it provides evidence against the strict form of the EMH. This suggests that stocks themselves are not completely efficient, yet alone accounting for changes in sovereign ratings. As such, ratings changes, if unanticipated, can have a significant effect on stocks.

The situation is however more complicated than at first would seem. As pointed out by Micu, Remolona, and Wooldridge (2006), relevant information to assess the creditworthiness of sovereigns are available daily. Thus, for sovereign ratings to be relevant they also need to be high frequency, but this needs to be balanced with a low volatility of credit ratings. This is because a low volatility of ratings instils investor confidence in ratings. So, in a complicated turn, rating agencies cannot release ratings too frequently in order to remain stable, but not being frequent means that they may not be relevant over and above publicly available information. As such, the EMH would hold. To address this issue, rating agencies have announcements, outlooks and rating changes, which all serve the same purpose, but provide a higher frequency, yet lower volatility.

In order to analyse the different rating events effects, a study by Micu et al. (2006) running from 2001 to 2005, made use of daily data on Credit Defaults Swaps (CDS) spreads. An event study was then conducted to see the timing of the effects of ratings announcements on these spreads. The results indicate that all types of ratings announcements have a statistically significant effect on CDS's spreads. The interesting result is that rating announcements are to a large extent anticipated, as some adjustment occurs before the rating announcement. It is however concluded that all rating announcements do include relevant pricing information, as they are not fully anticipated by the market. Thus, rating changes are found to add value and the EMH is found to hold, but only in the semi-strong form.

These results were confirmed to a large degree in a similar study by Ismailescu and Kazemi (2010), who used standard event study methodology to show the effects of credit ratings on CDS. Ismailescu and Kazemi (2010) find upgrades tend to contain new information, as 87% of positive rating announcements resulted in a decline in the event country CDS spread on day one. However, negative announcements were found to convey little new information. The overall result rejects the strict version of the EMH, in that CDS markets are efficient. These results are consistent with Micu et al. (2006) and shed light on the information content of ratings announcements for financial markets.

If, however, the EMH holds, then ratings can be highly detrimental to economies, possibly exacerbating economic upswings and downswings. Li et al. (2007) hypothesised that rating changes might lead to pro-cyclical behaviour, which is devastating during a financial crisis. They suggest that ratings agencies will only adjust their ratings after the crisis has occurred, leading to unnecessary capital outflows after the crisis has begun. They tested the hypothesis with the use of a panel regression on five countries hit hardest during the 1997

Asian crisis (Thailand, Indonesia, Malaysia, Philippines and Korea). After testing, they found no strong and consistent evidence of pro-cyclical behaviour by credit ratings agencies (Li et al., 2007).

Their findings are in line with Mora (2006), whose results find it questionable that ratings exacerbate the boom-bust cycle. Mora's (2006) study focused on East Asian nations and found that ratings are, if anything, sticky rather than exhibiting pro-cyclical behaviour. They then forecasted ratings, finding that actual ratings exceeded predicted ratings before a crisis, yet were accurate during a crisis period. This suggests that ratings were excessively high before a crisis and rating agencies were reacting to the bad news of a crisis thus pointing to pro-cyclical behaviour, but Mora (2006) also found ratings to react strongly to non-macroeconomic variables, suggesting that ratings reacted to news, rather than macroeconomic fundamentals during a crisis. As such, it was concluded that they are unlikely to exacerbate the business cycle.

In contrast, Kraussl (2005) finds evidence of pro-cyclicality in credit rating agencies. This was found by constructing an index which gave an indication of speculative market pressure (SMP Index), comprising changes in exchange rates, interest rates and the stock market. A standard event study methodology was employed, making use of Moody and S&P ratings. The period under observation was between January 1997 and December 2000, incorporating the dot com bubble. The findings show that changes in credit ratings had significant effects on the SMP index. Positive events lead to a decrease in the SMP index, whereas negative events lead to an increase. Empirically, rating announcements lagged changes in the SMP index, providing evidence that credit rating agencies react to market movements. Thus, they are concluded to, in fact, behave in a pro-cyclical manner and exacerbate the boom-bust cycle.

From the above, it can be shown that there are several ways that credit rating effects are transmitted to the domestic economy, such as effect on private investment and the sovereign ceiling channel. Also, the extent of the transmission depends on the efficiency of the financial markets. However, little has been discussed as to how credit rating effects are transmitted from a foreign nation to a domestic nation – typically referred to as cross border contagion and spill-over effects.

Ismailescu and Kazemi (2010) point to the common lender and international trade as possible transmission mechanisms for international contagion effects from credit ratings. The common lender approach suggests that most sovereigns have at least one, or even a few sovereigns in common from which they lend. As such, a rating change in the common lender sovereign will send shock waves through to all the nations to which it provides credit.

Ismailescu and Kazemi (2010), in their analysis of 30 nations, show the U.S. and Japan emerge as major lenders in their sample. They find that the majority of nations turn to the U.S. for capital while Asian nations turn to Japan for financing. This provides a strong basis for the theory, and they hypothesised that a positive credit rating event coming from a country that uses the same lender will lower the CDS premium of the non-event country. The second transmission (international trade flows) suggests that if a sovereign receives a better rating, it is more likely to engage in international trade, as it can service its payments for imports better and meet the demands of exports.

Ismailescu and Kazemi (2010) find that the common creditor is a statistically significant transmission mechanism for the effects of credit ratings across nations. It is also observed that CDS premiums of the non-event nation decline heavily in response to an upgrade in a country that shares the same lender. Trade flows are not found to be a significant transmission mechanism, however trade flows from the U.S. are shown to be a significant determinant of CDS premiums.

2.3 Ratings and crisis

Ratings agencies' most severe impact can come during times of financial crisis. An example of these impacts is the knock-on effects that occurred during the Asian crisis of 1997. As Reisen (1999) points out, ratings agencies largely failed to predict the Asian crisis. There was a small amount of concern by rating agencies as two Asian nations were downgraded by one notch ahead of the crisis. When the crisis hit however, sovereign ratings of Asian borrowers plummeted to junk status. The knock-on effect of this was that commercial banks could no longer issue letters of credit for local importers and exporters, foreign creditors called in their loans and institutional investors offloaded Asian assets. This is because most of the adjustment in ratings only occurred after the crisis erupted. It is argued that credit ratings largely reinforced the crisis instead of forecasting it as ratings are intended to do.

Bhatia (2002) argues that the reason rating agencies missed the looming crisis was because of their focus on macroeconomic fundamentals. Many Asian nations had sound macroeconomic fundamentals but little emphasis was placed on the Asian nations' international liquidity considerations and private sector weakness. These are the variables that eventually led to the crisis. In support, Li et al. (2007) note that even when it was public knowledge that an outbreak had occurred in July 1997, there was no warning signal issued by the rating agencies. In addition, rating agencies failed to predict the 1994-1995 Mexican crisis. The evidence, Larrain, Reisen, and Von Maltzan (1997) say, lies in the fact that the peso tumbled in value at December 20th 1994, but at December 22nd S&P still had Mexico's rating at one notch below investment grade with a positive outlook.

Reinhart (2002) finds that for emerging markets, the probability of having a currency crisis within 24 months of defaulting is about 84%. The probability of having a default within 24 months of a currency crisis is lower: about 58% for the entire sample, and 66% for emerging market economies. These results provide evidence of the link between currency crisis and defaults for emerging economies. Reinhart's (2002) findings suggest upgrades reduce the probability of a currency crisis, but are not statistically significant in their prediction of currency crises. This shows that credit rating agencies, while they are able to predict possible defaults, fail when predicting currency crises. This is despite the strong empirical link between currency crises and default. As such, this provides an explanation for rating agencies' oversight during the Mexican crisis of 1994-1995.

Not only are credit rating agencies failing to predict currency crises but they can have significant contagion effects during periods of financial crisis. Arezki and Candelon (2011) made use of a VAR model covering the 2008 financial crisis. They find that sovereign rating downgrades have statistically and economically significant spill-over effects, both across countries and financial markets. This implies that rating agencies' announcements could spur financial instability during times of financial crisis. Li et al. (2007) confirmed this result by splitting their sample between a crisis period and a tranquil period. In doing so, they found contagion amongst stock returns during the crisis period, but not during the tranquil period.

Furthermore, Li et al. (2007) find that stock markets reacted to rating changes in foreign countries more quickly than to the rating changes in their own country. This indicates the significant role of foreign country rating changes in exerting strong and swift contagion effects during periods of crisis, especially since investors are more attentive to assessing news developments in a cross-country environment during periods of crisis. It can be concluded that rating agencies not only struggle to forecast periods of financial instability, but that they also have significant contagion effects during crisis periods. However, this does leave room for improvement. Larrain et al. (1997) and Reisen (1999) both point to the possible smoothing impact that ratings agencies can have during these periods of crisis.

The main issue that ratings agencies can address, as suggested by Larrain et al. (1997), is the "Harberger externality". This effect is where private borrowers do not internalise the rising marginal social cost of their private borrowing that arises from the upward-rising supply of foreign capital. In simpler terms, private borrowers borrow too much capital when ratings are too high. As such, they could be increasing their borrowing even when the economy is in decline. Larrain et al. (1997) argue that if rating agencies could lead rather than lag financial markets by acquiring advanced knowledge and superior information, they could increase the cost of borrowing and reduce excessive lending before the "Harberger externality" sets in place.

Reisen (1999) supports this claim through the use of an event study that explores the link between credit ratings and sovereign yield spreads between 1989 and 1997, when the Asian crisis set in. He finds that ratings downgrades tend to widen yield spreads significantly, but part of the rise precedes the ratings downgrade. He however, finds no significant impact of upgrades on yield spreads. He concluded from the study that rating agencies have the potential to moderate euphoria among investors if they lead rather than lag the changes in yield spread. Larrain at al. (1997) and Reisen (1999) thus both argue that with advanced knowledge where ratings precede changes in financial markets and provide new information to markets, ratings agencies can avoid currency crises, moderate investor euphoria and ultimately dampen the effects of a financial crisis and its contagion amongst economies.

2.4 Ratings changes effects on bonds & stocks

In assessing the dynamics of ratings changes, an array of financial instruments and indices have been examined from CDS's to the financial openness of an economy. What needs to be specifically addressed however, are the effects of ratings changes on stocks and bonds, as these instruments are the focus of the current study.

Micu et al. (2006) make the following assumptions as to how credit ratings affect returns of bonds and stocks. Credit ratings have a direct effect on bonds as they relate directly to the risk inherent within a bond. If a downgrade or any other negative rating even occurs, there will be more risk associated with bonds, thus the risk premium will increase and bond spreads should widen (nominal rates increase). With equities, Micu et al. (2006) note that the possible effect is more ambiguous. The reaction depends on the reason for the ratings announcement. If the ratings downgrade is motivated by the fact that the issuers' financial prospective is deteriorating, such as their earnings are expected to decline, then this should lead to a decline in the stock price. If, however, the negative rating is due to an increase in the financial leverage of the firm, this should have the opposite effect. Share prices and returns should increase. Micu et al. (2006) state that the reason being that if the firm is more leveraged, there is a transfer of wealth from debt holders to equity holders. Increased leverage should lead to higher profits for the firm, assuming the firm is not in decline and operating as normal.

An empirical assessment of the effects of ratings on stocks was done by Barron, Clare, and Thomas, in 1997. Their results found that downgrades in long term bond ratings lead, on average, to a negative excess return of over -3.5% on the day of the announcement. After five days, the cumulative effect still remains at around -3%. This paper showed that rating changes can have significant effects for the individual stocks of a company. The results are in line with the hypothesis of Micu et al. (2006) that downgrades affect stocks through declines in expected earnings instead of through the leverage of the firm.

Brooks et al. (2004) provide further evidence of the effect in an event study that covered upgrades as well as downgrades. The study found that rating upgrades have no significant effect on abnormal stock returns, but downgrades had a significant decrease in average abnormal returns of -1.79% on the day that the downgrade occurred, a result that was less severe than those of Barron et al. (1997) but was consistent across developing and emerging nations.

As such, not only do ratings changes have significant impacts on stock returns but they also impact on bond returns. Cantor and Pacher in their 1996 study, analysed the effect of credit rating announcements on sovereign yield spreads. A regression of an average credit rating compiled by Cantor and Pacher on bond spreads was found to be statistically significant, when the average credit rating was excluded and macroeconomic variables such as Per capita income, GDP growth, inflation, fiscal balance, external balance, external debt, a development dummy variable, and default dummy were included. Only external debt, the development dummy and default dummy were statistically significant, but when the average rating was included with the macroeconomic variables, only the average rating was significant, suggesting that ratings encompassed all the relevant information that was needed to predict changes in the spread.

In a contrasting study, Larrain et al. (1997) made use of a granger causality test that looked at the impact of ratings announcements on yield spreads for 26 countries of which 10 were classified as emerging markets. Larrain et al. (1997) concluded that ratings caused changes in yield spreads and vice versa. Then with the use of an event study, they found that

29 days preceding a review for a possible downgrade, spreads rose by 25 percentage points. 29 days before a nation is put on positive outlook, yield spreads were found to fall by eight percentage points. In contrast to Cantor and Pacher's (1996) study, even though bond spreads were found to rise and fall before a negative/positive outlook, the effects were not found to be statistically significant. This is when the entire sample of countries is used, but there is a significant impact found when the event study is replicated only for emerging markets.

Ratings changes have been shown to have effects on the returns of bonds as seen above, but the severity of these effects depends on the investment grade of the bond. Jaramillo and Tejada (2011) found that investment grade status reduces financing costs significantly. With the use of a panel regression that incorporated 25 emerging market economies, Jaramillo and Tejada (2011) showed that, as expected, bond spreads for investment grade countries are 36% lower than for speculative grade nations. If, however, a nation is already in investment grade status then a one notch upgrade can lead to a 5% to 10% reduction on bond spreads. This is contrasted with the result that a one notch increase in their sovereign ratings leads to no reduction in bond spreads if the nation is already in speculative grade status. It can be concluded that bond spreads are more responsive to ratings changes when the bond is of a higher grade.

Larrain et al. (1997) added to these results in that a significant impact was found only for investment-grade, emerging-market securities. There was no significant effect of announcements on speculative, or investment grade bonds when both developed and emerging markets were considered. However, when only looking at emerging market investment grade bonds, there was a significant effect. Cantor and Pacher (1996) however, had a finding that objects to that of Jaramillo and Tejada (2011) and Larrain et al. (1997). Cantor and Pacher (1996) find that for speculative grade bonds, rating announcements had a statistically significant effect at the 1% level. Investment grade bonds however, had no significant effect from ratings announcements. Due to the conflict between findings, it is uncertain if speculative or investment grade bonds are more sensitive to rating changes.

What is of interest to the current paper, are the effects of credit rating changes on the volatility of stocks and bonds. Heinke (2006) studied the influence of rating classifications and watch listings on the credit spread volatility of plain vanilla bonds. The data consisted of German Eurobonds from international issuers that experienced a rating change between the period of 1984 and 1996. Heinke's (2006) results show that credit spread volatility is higher for bonds with a speculative grade as compared to investment grade bonds. In addition, the results show that for downgrades, credit spread volatility does indeed rise significantly while upgrade lead to significant decreases in credit spread volatility. However, Heinke's (2006) paper addresses credit spread volatility, and does not explicitly address bond volatility as this paper seeks to.

2.5 Bias towards downgrades

The literature shows that ratings changes do in fact, have an effect not only on the economy and private investment, but also on a nation's bond and stock returns. This effect is however, argued to be asymmetric with downgrades having a larger impact than upgrades.

Gande and Parsley (2005) state that the reasons why positive rating events might have no impact on bonds and stocks is that they are anticipated. Government has a higher incentive to leak or report on positive news such as positive rating changes and announcements as soon as talks have ended with ratings agencies. Thus, negative news would be stifled by government to maintain their image, and as such would come as more of a shock to the public when a rating change does occur. Another explanation as pointed out by Gande and Parsley is that ratings agencies have access to information as supplied by foreign governments. The rating agencies might be reluctant to lower rating or outlooks for the fear of being cut off from critical information supplied by governments that are not available to the public.

An event study conducted by Brooks et al. (2004) confirms this effect and shows that downgrades lead to larger abnormal stock returns than upgrades. More precisely Brooks et al. (2004) found that downgrades have a negative wealth impact on market returns. This was a long-standing study that covered the period from 1973 to 2001. Li et al. (2007) also found an asymmetric effect of downgrades and upgrades on stock returns in East Asia. Downgrades were found to have more of a significant effect than upgrades. Ferreira and Gama (2007) found that the effect of downgrades on stock returns are magnified for emerging markets. Sy (2002) used a panel data method to show this effect amongst 17 emerging markets and found that bond spreads are also affected by this asymmetric effect. Gande and Parsley (2005) confirm this asymmetric effect on bonds with the use of a panel regression, where credit events included both credit rating changes as well as watch lists. They find evidence of downgrades having a significant effect on bond spreads from a country's own downgrade, but not from their own upgrade.

Related literature to the asymmetric effect of ratings changes on emerging markets finds that while the effect of rating changes on other financial variables might still be asymmetric, it might not be of the same nature. Ismailescu and Kazemi (2010) make use of a standard event study methodology that consists of dollar denominated CDS's. Ismailescu and Kazemi's (2010) paper investigates the reaction of CDS spreads to credit rating changes and the cross-border spill-over effects of these rating changes. They find evidence that CDS's react immediately to positive ratings changes while negative ratings changes are found to have no significant effect as they are anticipated by the market (Ismailescu & Kazemi, 2010).

What can be drawn from Ismailescu and Kazemi's (2010) study, is that the asymmetric effect of downgrades having a significant impact on bonds and stocks might be unique to the financial instrument. As such, any conclusion drawn must be exclusive to the financial instrument being studied.

2.6 Contagion

There is an abundance of literature exploring the effects of contagion amongst developed and emerging economies. Caporale, Cipollini, and Spagnolo (2005) define contagion as being a significant increase in the degree of co-movement between stock returns in different countries. In this paper, contagion is defined as an unanticipated shock occurring in an event nation (where the shock occurs) that affects the financial variables of not only the event nation, but another non-event nation. Volatility spill-over refers directly to shocks in the event nation that increase the volatility of the non-event nation's financial variables. Shocks may include unanticipated rating changes as anticipated ratings changes will have no effect due to the EMH. Volatility spill-over is included in the concept of contagion, but contagion does not specifically refer to spill-over of volatility.

Many papers have emphasised the importance of contagion as a risk to the stability of financial markets. Christiansen, in a 2007 study, finds evidence of contagion between US and European bond markets. He uses a GARCH volatility spill-over model to show contagion effects from the US bond market, to the European bond market. He also examined the spill-over effects of the aggregate European bond market to individual European bonds. Christiansen (2007) finds the US spill-over is less severe than that of EMU countries' spill-over into the individual European markets. Billio and Caporin (2010), through the use of a simultaneous equation system with GARCH errors, identified mean relations and variance spill-over amongst American and Asian markets. Gallo and Otranto (2008) focused on the Asian stock markets of Hong Kong, South Korea, Malaysia, Singapore and Thailand, and finds evidence of volatility spill-over amongst the regional nations by making use of a Markov switching model. Note that these papers only confirm that contagion does occur across stocks and bonds but does not provide evidence of contagion resulting from credit ratings.

In order to test the empirics of credit ratings on contagion, Grande (2005) set out to show if credit rating changes, and changes in outlook caused financial contagion amongst bond spreads. Grande (2005) regressed the rating events of event nations on a non-event nations bond spreads. The results find that negative news for one country translates into increased spreads for all dollars denominated sovereign debt. However, positive events do not appear to induce statistically significant spill-over effects.

Ratings however, seem to induce contagion effects which are amplified by regional proximity. In an effort to dissect this specific dynamic of credit ratings, Kaminsky and Schmukler (2002) look at the effects of sovereign rating changes on bonds and stocks in emerging markets. Their findings suggest that spill-over effects are more pronounced on a regional level than amongst economic blocks that are non-regional. They find that within regions, upgrades and downgrades lead to an average increase in yield of 0.7 percentage points, whereas non-regional upgrades and downgrades triggered an average change in spreads of only 0.4 percentage points (Kaminsky & Schmukler, 2002). Ferreira and Gama (2007) confirm Kaminsky and Schmukler’s findings in that geographic distance is inversely related to the spill-over impact of an event nation’s stock exchange to non-event nation’s stock exchange. They find in particular, that the proximity of nations and being an emerging market amplifies the spill-over that results from a sovereign rating change.

Upgrades and downgrades can also lead to a decoupling and re-coupling effect on nations that are geographically close. Christopher, Kim, and Wu (2012) studied the effects of credit ratings on time varying stock and bond market correlations. They find the effects of rating changes on stock and bond markets to be heterogeneous. There is a positive relation between stock correlations and credit ratings, meaning upgrades lead to increases in stock correlations and downgrades reduce the correlation. This implies that a downgrade is seen as specific to a nation and leads investors to shift their funds from the downgraded nation to the surrounding countries (De-coupling effect). Positive rating changes on the other hand, lead to positive effects of returns on neighbouring nations and the event nation (re-coupling effect). (Christopher et al., 2012).

Contagion of credit ratings is also found to be more pronounced during times of financial instability. Li et al. (2007) split their regression results amongst the entire period examined, a crisis period during the 1997 Asian crisis and a tranquil period where no financial crisis occurred. They found that there was, indeed, contagion during the entire period, during the financial crisis period, but not during the tranquil period.

In a further analysis, Li et al. separated the contagion effects between ratings upgrades and downgrades. They found that countries' own upgrades and downgrades had a significant effect on the domestic economy, but the country only responded to downgrades from foreign nations and not upgrades. A one notch downgrade in a foreign nation was found to lead to an excessive reduction in the stock return of the domestic nation of -0.52% on the same day as the downgrade (Li et al., 2007). Kaminsky and Schmukler (2002) also found evidence of financial crisis exacerbating contagion effects across emerging markets as a whole.

As mentioned before, the nature of the asymmetric effect of downgrades and upgrades depends on the financial instrument. Ismailescu and Kazemi (2010), as well as Kang and Min (2016), found that only positive ratings changes had a significant effect on CDS's and this effect was also found to be significant to spill-over effects. This is contrasted with Li et al.'s (2007) finding where downgrades only have significant contagion effects on stocks, again highlighting that the nature of the asymmetric effect of contagion is unique to the financial instrument being evaluated.

With regards to volatility spill-over, Engle et al. (2012) made use a sophisticated collection of volatility models for eight East Asian countries from 1995 to 2006. They found interdependence of volatility amongst the eight nations and a build-up of volatility transmission during the 1997 Asian crisis. This provides evidence of volatility spill-over across emerging markets, but Afonso et al. (2014) provide evidence of volatility spill-over resulting specifically from credit rating changes. Afonso et al. (2014) conducted a panel regression encompassing developed and developing EU nations, with data ranging from 1995 to 2002. They studied the effects of credit ratings on stock and bond market volatilities and found contagion of volatility spill-overs to be present. Amongst European financial markets, they found that upgrades lead to a decrease in volatility, while downgrades lead to an increase in volatility across nations.

3 CHAPTER 3: METHODOLOGY

3.1 Data

The data used for ratings changes were obtained from Bloomberg and includes ratings changes for nine different rating agencies. In addition to the three main American ratings agencies (Moody's, Standard & Poor and Fitch), the data includes ratings changes from other agencies (DBRS, R&I, Japan CRA, Dagong, Duff & Thompson). This is vital because the majority of papers cited only used the three main ratings agencies (S&P, Moody's, and Fitch). The reason for this is that, as Reisen (1999) notes, the three market leaders cover approximately 80% of sovereign credit ratings. However, for a holistic view of the effects of ratings agencies, the study utilises the use of a comprehensive data set, incorporating six additional agencies.

The data is daily data and has run for 26 years over the period of 1 January 1990 to 16th September 2016. The credit rating data was then transformed into discrete dummy variables in order to reflect the decisions of ratings agencies. On a given date *t* and country *i* the dummy variables *up* and *down* assume the following values:

$$up_{i,t} = \begin{cases} 1, if\ an\ upgrade\ of\ any\ agency\ occurs \\ 0, Otherwise \end{cases} \quad Down_{i,t} = \begin{cases} 1, if\ a\ downgrade\ of\ any\ agencyoccurs \\ 0, otherwise \end{cases} \tag{1}$$

A dummy variable for *up* and *down* was used instead of a numerical scale because the credit ratings of agencies are assigned by rating committees, where a large dose of judgment is used. In addition, some of the criteria for rating a sovereign are not quantitative, let alone quantifiable (FitzGerald, 2009). As such, to avoid any biases that might occur from ordinal ranking, dummy variables are used to indicate an upward or downward movement in a sovereign's credit rating. Contagion credit rating dummy variables for the analysis of volatility spill-over are manifested below.

$$up^{-i}{}_{i,t} = \begin{cases} 1, if\ an\ upgrade\ of\ any\ agency\ occurs\ in\ any\ other\ nation \\ 0, Otherwise \end{cases} \tag{2}$$

$$down^{-i}{}_{i} = \begin{cases} 1, if\ an\ downgrade\ of\ any\ agency\ occurs\ in\ any\ other\ nation \\ 0, Otherwise \end{cases}$$

The World Bank classifies countries into four different categories: low-income (LI), lower middle income (LMI), upper middle income (UMI) and high-income (HI). All LI, LMI and UMI economies are categorised as emerging markets. For the purpose of this study, emerging markets were classified as lower and middle income, in accordance with the World Bank (The World Bank, 2016).

Only 31 of the 94 emerging market countries for which data was attainable had sufficient capital markets that were deep and liquid enough to draw empirical results. The 31 countries required well-functioning stock and bond markets and in addition, were required to have had at least one sovereign ratings change by S&P over the period being assessed in order to be included in the study. The 31 countries are Brazil, Bulgaria, China, Croatia, Czech Republic, Colombia, Egypt, Greece, Hungary, Israel, India, Indonesia, Jamaica, Lithuania, Malaysia, Mexico, Nigeria, Pakistan, Panama, Peru, Philippines, Poland, Romania, Russia, Slovakia, Slovenia, South Africa, Thailand, Turkey, Ukraine, and Venezuela.

The data set comprises daily stock and bond indices for the 31 countries and was obtained from Bloomberg. Daily data was used as with an increase in the frequency of data comes an increase in persistence (Nelson, 1991). Daily data thus allowed for a more accurate analysis of the persistence of credit rating shocks from one day to the next. These indices were indicative of the stock or bond market, as a whole, in the respective country and the bond indices are government issue 10-year bond indices.

3.2 Empirical Method

A fixed effects panel data method is used in order to make efficient use of data that is both cross sectional and time series, by providing a single equation describing the relationship amongst a multiple of countries and over many time periods. It allows for results to be drawn where the data may be lacking variability due to the nature of ratings changes being infrequent. In addition, a fixed effect panel regression allows for the isolation of variables that are not common amongst countries, giving a true measure of statistical significance (Brooks, 2014).

In addition, an EGARCH (Exponential generalised autoregressive conditional heteroscedasticity) model is used to generate the stock and bond volatilities that are fed into the fixed effects panel data estimation - Heteroscedasticity meaning non-constant variance. This model is utilised at it accounts for the leverage effect found in financial time series where negative shocks to returns increase the predictable volatility to a greater extent than do positive shocks of a similar magnitude (Asai & McAleer, 2011). All regressions are done with Eviews statistical package.

Stock market returns ($r^{S}{}_{i,t}$) at time t for each country are defined as the differenced log returns of the stock price indexes and are thus of the first order. For the bond indices, returns ($r^{B}{}_{i,t}$) are defined as the difference in the log yields of the bond indices. In order to model the volatilities of the bond and stock indices, an ARCH model could be useful as it allows for the modelling of heteroskedastic financial time series, which is often the case with financial return series. ARCH models also allow for the modelling of volatility that occur in bursts (Brooks, 2014). However, a GARCH model, as suggested by Bollerslev (1986), provides a marginally better fit than that of an ARCH model. Neither of these models is utilised in this study.

Moreover, Nelson (1991) points out some of the features of financial time series that GARCH models are unable to account for. Firstly, researchers have found a negative correlation between current returns and future returns volatility, where negative returns have a more severe impact than positive return shocks. The reason, as stated by Black (1976), is that if the stock price of a firm decreased, this inevitably means that its capital structure will change and its leverage will have increased. Investors then view this as being a riskier stock and as such, downwards revisions in the returns of a stock lead to larger effects on volatility than upwards shocks. Nelson (1991) and Ding et al. (1993), using daily data on stock index returns, find that large positive as well as negative unanticipated returns lead to an upward revision in the conditional volatility, although negative shocks of similar magnitude lead to larger revisions. GARCH models rule out the possibility of modelling this asymmetric feature as they assume a symmetric relationship between past volatility and future volatility.

Secondly, GARCH models impose parameter restrictions such as having no negative coefficients. This however, will restrict the dynamics of the conditional variance process and can often be violated.

Thirdly, Nelson (1991) points to the difficulties in interpreting the persistence of financial time series modelled by a GARCH model. The reason is that GARCH models shocks may persist in one norm and then die out in another.

In order to calculate the daily parametric volatilities of the bond and stock returns in this study, the EGARCH model is used. As mentioned before, shocks in financial time series volatility tend to have an asymmetric effect on future volatility for which the GARCH model does not account. This is known as the leverage effect where negative shocks to returns increase the predictable volatility to a greater extent than do positive shocks of a similar magnitude (Asai & McAleer, 2011).

Nelson (1991) points to the main advantage of the EGARCH models in that they allow for asymmetries in the return data. The model allows for positive and negative ratings changes to have different effects on volatility, and thus factors in the asymmetric volatility phenomenon. Furthermore, the EGARCH model also addressed the second issue with GARCH models, where they impose restrictions on the coefficients to ensure volatilities are non-negative. To correct for this, EGARCH models make use of the log of the conditional variance $\ln(\sigma^2{}_t)$. This ensures positive values for all conditional volatiles. The EGARCH model deals with the third issue by providing a coefficient whose explicit purpose is to give a measure of persistence, providing ease of interpretation (Nelson, 1991).

For the EGARCH specification, we assume that stock returns follow a random walk and are represented by the following specification $r_{i,t+1} = \mu_i + \varepsilon_{i,t+1}$ .The error terms comprise stock and bond return volatility in addition to $z_{i,t}$ which are i.i.d t-distributed error terms with mean zero. $\varepsilon_{i,t+1} = \sigma_{i,t+1} z_{i,t+1}$ where $z_{i,t} = {}^{\varepsilon_{i,t}}/_{\sigma_{i,t}}$. The EGARCH (1,1) specification comes from the original formulation as per Nelson (1991).

$$\ln(\sigma^2{}_t) = \omega + \beta \ln(\sigma^2{}_{t-1}) + \gamma \frac{\mu_{t-1}}{\sqrt{\sigma^2{}_{t-1}}} + \alpha \left[\frac{|\mu_{t-1}|}{\sqrt{\sigma^2{}_{t-1}}} - \sqrt{\frac{2}{\pi}} \right] \tag{3}$$

In equation (3) ω serves as a constant while β serves as a measure of persistence showing that past volatility shocks will have an effect on future volatility. The coefficient γ gives the sign of the expected relationship between stock returns and volatility and it will be negative if higher returns lead to lower future volatility. A negative result was found in the empirics of this study. α is the coefficient that measures the asymmetric volatility phenomena and is expected to show that negative returns will have a larger effect on volatility than positive returns of the same magnitude. If the coefficient α is positive while the coefficient γ is negative, then a negative shock has a higher impact on volatility than a positive shock because $|\gamma - \alpha| \geq |\gamma + \alpha|$(Nelson, 1991). It should be noted that the only information used for the estimation in equation (3) is the stock and bond returns. No upgrade or downgrade information has been utilised, a yet. The results of the EGARCH estimation are reported in Table 2 for each of the 31 countries.

In order to study the reaction of stock and bond market volatilities to ratings upgrades and downgrades, a fixed effects panel data regression is used. This is a common method used in the study of credit ratings and authors such as Erdem and Varli (2014), Montes et al. (2016), Chen et al. (2013), Li et al (2007), Grande (2005), Kaminsky and Schmukler (2002) all make use of a panel regressions. The specific formula for the Panel regression use in this study is shown in Eq (4).

$$\log(\sigma_{i,t}) = \mu_i + \sum_{j=0}^{k} \lambda_j down_{i,t-j} + \sum_{j=0}^{k} \alpha_j up_{i,t-j} + \beta \log(\sigma_{i,t-1}) + \zeta^T X_{t-1} + \varepsilon_{i,t} \qquad (4)$$

The dependant variable $\log(\sigma_{i,t})$ are the conditional volatilities for stocks and bonds, filtered from the specification in Eq (3). μ_i are the country fixed effects and $up_{i,t-j}$ *and* $down_{i,t-j}$ are the dummy variables that were specified in Eq (1); representing the upgrades and downgrades of any ratings agency for a given country. The dummy variables are lagged in order to show persistence in the effects of upgrades and downgrades on volatilities. The coefficient β gives a measure or persistence and $X_{t-1}$and is a vector of control variables such as dummy variables for daily, weekly and annual effects. The results of Eq (4) are displayed in Table 3.

The effects of contagion amongst countries is investigated by including dummy variables for upgrades and downgrades, where the variable includes upgrades or downgrades from every other nation other than itself. This way the effects of ratings shocks in other nations on the host nations stock and bond volatilities can be investigated. The specification of the contagion model is as follows:

$$\log(\sigma_{i,t}) = \mu_i + \sum_{j=0}^{k} \lambda_j down_{i,t-j} + \sum_{j=0}^{k} \alpha_j up_{i,t-j} + \sum_{j=1}^{k} \phi_j up^{-i}{}_{i,t-j} + \sum_{j=1}^{k} \delta_j down^{-i}{}_{i,t-j} + \beta \log(\sigma_{i,t-1}) + \zeta^T X_{t-1} + \varepsilon_{i,t} \qquad (5)$$

Eq (5) is specified the same as Eq (4) with $\log(\sigma_{i,t})$ representing the conditional volatilities, μ_i representing country fixed effects, $up_{i,t-j}$ *and* $down_{i,t-j}$ reflecting the ratings decisions of ratings agencies and X_{t-1} are control variables for daily, weekly and annual effects. In addition, $up^{-i}{}_{i,t-j}$ *and* $down^{-i}{}_{i,t-j}$reflect upgrades and downgrades in any other country other than country *i*. The magnitude of the contagious upgrades and downgrades are reflected by the coefficients $\phi_j \& \delta_j$ which are lagged in order to show the persistence of the contagious effects. The results of Eq (5) are displayed in Table 5 and are split amongst the total sample of emerging markets according to continent. Thus, contagious effects are shown separately for South America, Asia and Europe. Europe, for example, has the contagious dummy variables ${up^{-i}}_{i,t-j}$ and ${down^{-i}}_{i,t-j}$ which only reflect upgrades and downgrades in any country other than country *i* for the Europe area only.

4 CHAPTER 4: EMPIRICAL RESULTS

Table 1: Average of stock and sovereign bond market volatilities for different rating categories

Soverign Rating	Stock Market Volatility	Bond Market Volatility
AA	0.0001190369	
AA-	0.0000640378	0.0008683215
A+	0.0001000095	0.0001480477
A	0.0001401286	0.0001709438
A-	0.0001777909	0.0001539859
BBB+	0.0002916591	0.0001540370
BBB	0.0001869245	0.0001753367
BBB-	0.0003225997	0.0000793762
BB+	0.0001996284	0.0003059018
BB	0.0001929389	0.0000800855
BB-	0.0001783656	0.0001052823
B+	0.0003519218	0.0001161597
B	0.0004547015	0.0001512624
B-	0.0003523360	0.0001604949
CCC+	0.0002606544	0.0003827658
CCC	0.0005642285	0.0011027135
CCC-	0.0011987385	0.0120476322
SD	0.0028369074	0.0003907928

Note: This table reports the average daily volatilities of stock and sovereign bond indices, historical volatilities for each of the different rating categories (AA,..,SD). The volatilities are calculated by first calculating the variance for the period in which the country was in a specified ratings category. These variances were then summed and divided by the number of periods in which each and all the countries were in a specific ratings category, to give the average daily volatility for that ratings category.

In Table 1, the average volatilities for both stocks and bonds are reported in order to assess if a lower rating will on average lead to more volatility in stocks and bonds. From the results, there seems to be a clear increase in volatility of stocks, as the country's average credit rating deteriorates. However, this pattern is not as clear amongst the bond markets. The results are in line with studies such as Heinke (2006), who finds evidence of bonds of a speculative grade having higher volatilities than investment grade. Jaramillo and Tejada (2011) highlight this as a stylised fact, where sovereigns that have better credit ratings tend to have lower spreads. This supports the results in Table 1 if bonds spreads can be assumed to proxy for bond volatility.

From the results, it is concluded that on average of the emerging markets, speculative grade nations experience approximately 2.76 times more volatility in their stock markets than their investment grade counterparts. As for bond markets, while there is no clear pattern or increased volatility with a decreased credit rating, speculative grade nations experience 4.93 times more volatility in their bond markets, than investment grade nations do. It should be noted that an AAA rating was excluded due to lack of emerging markets of an AAA rating. The same applies for AA rated bonds in our emerging market data set.

Table 2: Summary of EGARCH estimation results Eq (3)

Country	Slope γ (C4)		Asymmetry α (C3)		Persistence β (C5)		Obs.
Stock Market							
Brazil	-0.051	***	0.217	***	-0.184	***	9755
Bulgaria	-0.009	***	0.171	***	0.994	***	5806
China	0.014	***	0.154	***	0.992	***	9403
Colombia	-0.058	***	0.230	***	0.961	***	5177
Croatia	-0.007	***	0.161	***	0.991	***	5208
Egypt	-0.019	***	0.132	***	0.966	***	6833
Greece	-0.011	***	0.070	***	0.998	***	9755
Hungary	-0.027	***	0.184	***	0.973	***	9389
India	-0.015	***	0.113	***	0.995	***	9755
Indonesia	-0.013	***	0.138	***	0.993	***	9755
Israel	-0.038	***	0.091	***	0.992	***	9024
Jamaica	0.027	***	0.229	***	0.963	***	9755
Lithuania	-0.004	***	0.108	***	0.994	***	6100
Malaysia	-0.034	***	0.126	***	0.996	***	9755
Mexico	-0.049	***	0.053	***	0.994	***	8276
Nigeria	0.024	***	0.183	***	0.986	***	6832
Pakistan	-0.032	***	0.148	***	0.970	***	9083
Panama	0.011	***	0.554	***	-0.191	***	9025
Peru	-0.011	***	0.212	***	0.983	***	9754
Philippines	-0.036	***	0.111	***	0.990	***	9755
Poland	-0.003	***	0.121	***	0.993	***	9285
Romania	-0.015	***	0.179	***	0.984	***	6934
Russia	-0.030	***	0.126	***	0.993	***	6934
Slovakia	0.011	***	0.125	***	0.973	***	8403
Slovenia	-0.029	***	0.201	***	0.968	***	4917
South Africa	-0.060	***	0.106	***	0.990	***	7749
Thailand	-0.040	***	0.139	***	0.983	***	9755
Turkey	-0.007	***	0.108	***	0.995	***	9755
Ukraine	-0.009	***	0.178	***	0.984	***	6822
Venezuela	0.027	***	0.224	***	0.942	***	8296
Bond Market							
Brazil	0.077	***	0.137	***	0.861	***	3458
Bulgaria	0.040	***	0.167	***	0.093	***	3098
China	-0.002	***	0.048	***	0.952	***	3959
Colombia	0.007	***	0.176	***	0.888	***	5335
Croatia	0.609	***	1.414	***	0.248	***	388
Egypt	-0.270	***	-1.018	***	0.013		1725
Greece	-0.057	***	0.241	***	-0.333	***	3486
Hungary	0.013	***	0.145	***	0.983	***	3486
India	-0.009	***	0.115	***	0.983	***	6456
Indonesia	0.071	***	0.139	***	0.964	***	4805
Israel	-0.041	***	0.374	***	-0.437	***	2004
Jamaica	-0.048	***	0.124	***	0.995	***	3990
Lithuania	0.506	***	0.996	***	0.409	***	925
Malaysia	0.118	***	0.163	***	0.786	***	6174
Mexico	0.049	***	0.342	***	0.698	***	2353
Nigeria	-0.084	***	-0.021	***	0.968	***	1806
Pakistan	-0.141	***	0.204	***	-0.266	***	4474
Panama	-0.062	***	-0.006	***	0.956	***	1922
Peru	-0.031	***	0.272	***	-0.340	***	3830
Philippines	0.089	***	0.065	***	0.880	***	6625
Poland	0.072	***	0.063	***	0.883	***	6322
Romania	-0.021	***	0.132	***	0.992	***	1926
Russia	0.142	***	0.105	***	0.892	***	2352
Slovakia	-0.060	***	0.010	***	1.003	***	5202
Slovenia	-0.049	***	0.231	***	0.978	***	2017
South Africa	0.090	***	0.128	***	0.894	***	6163
Thailand	0.018	***	0.318	***	-0.147	***	6083
Turkey	0.005	***	0.092	***	0.989	***	2424
Ukraine	0.102	***	0.028	***	0.975	***	2024
Venezuela	0.085	***	0.167	***	0.924	***	3899

Note: Table 2 shows the results of the estimation of the EGARCH model in Eq (3). Obs indicates the number of observations included in the regression.

* Represents statistical significance at 10%.

** Represents statistical significance at 5%.

*** Represents statistical significance at 1%.

Table 2 reports the EGARCH results for each of the individual nations and separates the results amongst stocks and bonds. From the results, we can see that due to the high significance of the coefficient α there is indeed an asymmetric relationship between returns and volatility of returns for both stocks and bonds. From the methodology, it is known that if the coefficient α is positive while the coefficient γ is negative, then a negative shock has a higher impact on future volatility than a positive shock. This is seen to be the case in the results for stocks and as such, negative return shocks are in fact more significant that positive return shocks. For bonds, however, the result is mixed with some bonds showing positive returns shocks to have more of a significant effect than negative return shocks. Overall, the results are in line with the findings of Nelson (1991), Ding et al. (1993) and Black (1976). The coefficient β is statistically significant for stock and bonds and as such, returns can be concluded to have persistent effects on future returns volatility.

Table 3: Estimation results of stock and bond market volatilities with 3 main agencies (S&P, Moody's and Fitch) Eq (4)

Events		*Stock Market*		Bond Market	
Upgrade	*t*	0.0000014656		0.0000235828	
		(0.320)		(1.308)	
	t - 1	0.0000008901		0.0000492918	***
		(0.193)		(2.641)	
	t - 2	0.0000004983		0.0000088437	
		(0.108)		(0.473)	
Downgrade	*t*	0.0000260704	***	0.0001556258	**
		(5.541)		(10.197)	
	t - 1	0.0000073098		-0.0001157079	*
		(1.553)		(-7.576)	
	t - 2	0.0000030660		0.0000336933	
		(0.651)		(2.207)	
Lagged Volatility		0.9764291517	***	0.632598673	***
		(1978.807)		(165.514)	
R^2		0.965919[0.154151]		0.754479[0.571035]	
Observations		189612		39216	
Countries		23		10	
#Upgrades		160		61	
#Downgrades		166		66	
F - Test 3rd Lag		67258.06945	***	2270.878523	***
F - Test 5th Lag		63877.89508	***	2111.495515	***

Note: This table reports the estimation results that correspond to the regression equation in Eq (4). The t-statistics for the statistical significance of the estimated coefficients are reported below their corresponding coefficients. Negative t-stats are reported in parenthesis. Control variables, X, in Eq (4) include daily, monthly and annual dummies. P-values (F -tests) for joint statistical significance are also reported in the table.

* Represents statistical significance at 10%.

** Represents statistical significance at 5%.

*** Represents statistical significance at 1%.

Table 3 reports the estimation results for Eq (4) using two lags for the three main rating agencies. Two lags have found to be sufficient to capture the dynamics of rating changes and their effects over time (Afonso et al., 2014).

An asymmetric effect is observed for stocks, showing that rating downgrades have a significant effect on stock volatilities while upgrades have no effect. This provides confirmation that downgrades not only affect stock returns but also continue to influence the second moments of these variables. This finding is in line with Afonso et al.'s (2014) study of the EU stock market. In addition, these results provide evidence to the theory advanced by Gande and Parsley (2005), in that rating downgrades are unanticipated, because governments are reluctant to reveal negative rating news. However, when it comes to bonds, no asymmetric effect is observed. Upgrades and downgrades are shown to have a statistically significant effect on the variance of bonds. This is contrasted with Afonso et al. (2014) who finds an asymmetric effect with bonds and no effect of upgrades on bond volatility.

The results add further findings to studies such as Brooks et al. (2004), Li et al. (2007), Sy (2002), Gande and Parsley (2005), which find that downgrades are likely to have a significant effect on bond and stock returns in comparison to upgrades. These results show that, in addition, volatility is affected by rating changes. It should be noted that the size of the coefficients is close to negligible, but still remains statistically significant for downgrades and upgrades for bonds. An explanation could be that ratings changes tend to cluster as the same point in time further detracting from each individual agency's rating change significance.

In terms of the direction of the effects, upgrades increase bond volatility after a one day lag while downgrades' effect on bond volatility is more ambiguous, increasing bond volatility on the event day and then decreasing bond volatility after a one day lag. For stocks, downgrades are found to increase stock volatility on the event day.

In both the regressions, the full 31 countries are not included, the reason being that while the excluded nations had sufficient data for stock and bond indices there was not enough variation in some of the nations' data, or there were collinearity issues, leading to a near singular or singular matrix result for the regression. As such, nations that exhibited this error were excluded from the regression. The R-squared in both regressions are also found to be particularly high with a value of 97% for stocks and 75% for bonds. This is the result of the persistence of shocks in stocks and bond returns leading to high R-squared values.

Table 4: Estimation results of stock and bond market volatilities with nine agencies Eq (4)

Events		*Stock Market*		Bond Market	
Upgrade	*t*	0.0000005830		0.0000000667	
		0.138		0.005	
	t-1	0.0000006071		0.0000016346	
		0.143		0.108	
	t-2	-0.0000000292		0.0000049870	
		(0.007)		0.330	
Downgrade	*t*	0.0000267774	***	0.0000029821	
		6.778		0.207	
	t-1	0.0000070491	*	0.0000017504	
		1.785		0.122	
	t-2	-0.0000040594		0.0000411765	***
		(1.027)		2.861	
Lagged Volatility		0.9794630127	***	0.986917808	***
		2057.358		1170.429	
R^2		0.971		0.977	
Observations		177201		42087	
Countries		22		18	
#Upgrades		132		90	
#Downgrades		146		75	
F-Test		83423.77911	***	38636.5891	***

Note: This table reports the estimation results that correspond to the regression equation in Eq (4). The t-statistics for the statistical significance of the estimated coefficients are reported below their corresponding coefficients. Negative t-stats are reported in parenthesis. Control variables, X, in Eq (4) include daily, monthly and annual dummies. P-values (F -tests) for joint statistical significance are also reported in the table.

* Represents statistical significance at 10%.

** Represents statistical significance at 5%.

*** Represents statistical significance at 1%.

Table 4 reports the estimation results for Eq (4) with the use of rating changes from nine rating agencies. An asymmetric effect is observed, showing that rating downgrades have a significant effect on stock and bond volatilities while upgrades have no effect. This provides further confirmation that downgrades not only affect stock and bond returns but also continue to influence the second moments of these variables.

These results are directly in line with those found in Afonso et al.'s (2014) study of the EU stock and bond market. They also reinforce the results of papers such as Brooks et al. (2004), Li et al. (2007), Sy (2002), Gande and Parsley (2005) in that downgrades are likely to have a significant effect on bond and stock returns in comparison to upgrades. The results in Table 4 do however, vary from those found in Table 3. When nine rating agencies are used, there is no evidence of upgrades having a statistically significant effect on bond volatility, however when only the three main rating agencies were utilised (S&P, Moodys and Fitch) evidence of upgrades having an effect on bond volatility is observed.

In terms of the direction of the effect, downgrades increased stock volatility on the event day, and in the second day. For bonds, downgrades only increased the volatility on the third day lag. In both the regressions, the full 31 countries are not included as some countries' data exhibited a singular matrix error. As such, nations that exhibited this error were excluded from the regression. The R-squared in both regressions are also found to be particularly high with a value of 98% for stocks and 99% for bonds. This is the result of the persistence of shocks in stocks and bond returns leading to high R-squared values. It is interesting to note that 2008 was one of the only years controlled for that held any statistical significance and was significant at the 1% level.

Table 5: Estimation results of regressions of stock and bond market volatilities Eq (4), alternative volatility measures using 9 rating agencies

Events		*Stock Market*				*Bond Market*			
		GJR GARCH		EGARCH Gaussian Distribution		GJR GARCH		EGARCH Gaussian Distribution	
Upgrade	*t*	-0.0000050171		0.0000005830		0.0000143108		0.0000000667	
		(0.352)		0.137		0.332		0.004	
	t - 1	-0.0000011182		0.0000006071		0.0000580708		0.0000016346	
		(0.078)		0.143		1.328		0.108	
	t - 2	-0.0000004421		-0.0000000292		0.0000102742		0.0000049870	
		(0.030)		(0.006)		0.253		0.329	
Downgrade	*t*	0.0000403898	***	0.0000267774	***	0.0001537164	***	0.0000029821	
		2.858		6.777		5.026		0.207	
	t - 1	0.0000002814		0.0000070491	*	0.0001683575	***	0.0000017504	
		0.019		1.784		5.507		0.121	
	t - 2	0.0000107875		-0.0000040594		0.0000585840	*	0.0000411765	***
		0.736		(1.027)		(1.915)		(2.860)	
Lagged Volatility		0.9679182591	***	0.9794630127	***	0.7608724157	***	0.9869178080	***
		1854.57		2057.35		289.97		1170.42	
R^2		0.946		0.971		0.652		0.977	
Observations		230328		177201		60672		42087	
Countries		28		22		27		18	
#Upgrades		157		132		153		90	
#Downgrades		158		146		156		75	

Note: This table reports the estimation results that corresponds to the regression equation in Eq (4) using volatilities that are filtered based on: (i) GJR-GARCH model (Glosten et al., 1993), (ii) EGARCH model with the Gaussian distribution (Nelson, 1991). Control variables, X, in Eq (4) include daily, monthly and annual dummies. Negative t-stats are reported in parenthesis.

* Represents statistical significance at 10%.

** Represents statistical significance at 5%.

*** Represents statistical significance at 1%.

As a robustness check, an alternative volatility model is estimated, namely the GJR-GARCH (Glosten, Jagannathan, & Runkle, 1993) model and compared to the previously estimated EGARCH model. The GJR-GARCH model allows for possible asymmetries in the effect of current return shocks on conditional volatility (the leverage effect). The model however, still imposes non-negativity constraints, as is a feature with GARCH models (Brooks, 2014). For both of the models, the corresponding volatilities are filtered and then used to estimate Eq (3). As can be seen, the results are robust when compared to Table 4 with upgrades being found to have no statistically significant effect on emerging market bond and stocks, while downgrades are found to have a highly significant effect within the three day window.

Table 6: Estimation results of regressions of stock and bond market volatilities with 3 main agencies (S& P, Moody's and Fitch) Eq (5)

Events		*Stock Market*								*Bond Market*					
		Emerging Markets		South America		Europe		Asia		Emerging Markets		Europe		Asia	
Upgrade	*t*	0.0000015261		0.0000051547		-0.0000009214		0.0000042445		0.0000237623		-0.0000001477		0.0000035844	
		(0.333)		(0.200)		(-0.160)		(0.470)		(1.318)		(-0.003)		(1.057)	
	t - 1	0.0000009595		-0.0000020255		-0.0000003461		0.0000091008		0.0000492474		0.0001395167		0.0000149798	
		(0.208)		(-0.078)		(-0.059)		(1.032)		(2.639)	**	(2.986)	***	(4.426)	***
	t - 2	0.0000004945		-0.0000021049		0.0000061098		-0.0000045986		0.0000088333		0.0000909790		0.0000004465	
		(0.107)		(-0.082)		(1.050)		(-0.510)		(0.473)		(1.946)		(0.1319)	
Downgrade	*t*	0.0000262206	***	-0.0000133138		0.0000048367		0.0001240709	***	0.0001556199	***	0.0002797113	***	0.0000167237	**
		(5.573)		(-0.457)		(0.853)		(11.534)		(10.196)		(9.737)		(2.477)	
	t - 1	0.0000070312		-0.0000097270		0.0000087022		0.0000020797		-0.0001155459	***	-0.0000326729		0.0000084633	
		(1.494)		(-0.334)		(1.535)		(0.1912)		(-7.565)		(-1.133)		(1.253)	
	t - 2	0.0000028633		0.0000188830		-0.0000002540		0.0000058076		0.0000338422	**	0.0000332060		-0.0000033701	
		(0.608)		(0.648)		(-0.044)		(0.534)		(2.217)		(1.155)		(-0.499)	
	t	-0.0000014520	*	-0.0000017473		-0.0000019962		-0.0000018207		-0.0000018071		-0.0000025524		-0.0000002901	
Upgrade Others		(-1.724)		(-0.359)		(-1.516)		(-1.149)		(-0.464)		(-0.251)		(-0.448)	
	t - 1	-0.0000013269		0.0000019636		-0.0000012363		-0.0000017818		0.0000005505		0.0000062345		0.0000002100	
		(-1.569)		(0.402)		(-0.935)		(-1.120)		(0.140)		(0.6104)		(0.322)	
	t - 2	-0.0000011624		-0.0000069427		-0.0000009951		0.0000000262		-0.0000037862		-0.0000011029		0.0000002985	
		(-1.374)		(-1.421)		(-0.752)		(0.016)		(-0.964)		(-0.108)		(0.459)	
	t	-0.0000007199		-0.0000078201		-0.0000031912	**	0.0000041606	**	0.0000034465		0.0000008866		0.0000004742	
Downgrade Others		(-0.777)		(-1.479)		(-2.152)		(2.431)		(0.807)		(0.077)		(0.592)	
	t - 1	0.0000052608	***	-0.0000041053		0.0000062824	***	0.0000111931	***	0.0000022697		0.0000059614		-0.0000002348	
		(5.684)		(-0.776)		(4.240)		(6.538)		(0.532)		(0.520)		(-0.293)	
	t - 2	0.0000037704	***	0.0000032006		0.0000070694		-0.0000008130		-0.0000020712		-0.0000087346		0.0000002607	
		(4.074)		(0.605)		(4.772)		(-0.474)		(-0.485)		(-0.760)		(0.325)	
		0.9763944539	***	0.9455351809	***	0.9773085371	***	0.98769128	***	0.6325964144	***	0.020313488	**	0.866170642	***
Lagged Volatility		(1978.811)		(389.843)		(1013.902)		(1493.703)		(165.501)		(2.184)		(182.643)	
R^2		0.964254[0.225710]		0.911448[0.163941]		0.968231[0.281813]		0.980445[0.176102]		0.754494[0.571070]		0.680362[0.675227]		0.874684[0.168035]	
Observations		189612		18050		47640		54300		39216		11379		6049	
Countries		23		3		6		6		10		3		3	
#Upgrades		96		14		33		23		61		15		8	
#Downgrades		89		9		36		16		66		25		8	
#Upgrades (Other)		2993		338		640		783		1682		387		260	
#Downgrades (Other)		2518		330		531		664		1405		315		219	

Note: Table 5 reports the estimation results that correspond to the regression in Eq (5). Negative t-stats are reported in parenthesis. Control variables, X, in Eq (5) include daily, monthly and annual dummies.

* Represents statistical significance at 10%.

** Represents statistical significance at 5%.

*** Represents statistical significance at 1%.

Table 6 reports the results of the estimation for stock and bond markets but with contagion effects considered as well. The contagion effects are represented by the coefficient ϕ_j for upgrades under the heading “upgrade others” and δ_j for downgrades under the heading “Downgrade others”. It is found that contagion tends to magnify when countries are geographically close rather than when they are part of an economic block (Kaminsky & Schmukler, 2002). As a result of this fact, the results are split amongst the continents of South America, Europe and Asia including a regression for all emerging markets.

When looking at emerging markets as a whole, there is no evidence found of upgrades having an effect on stock volatility while downgrades are found to have a statistically significant effect. Both upgrades and downgrades from other nations are found to have a contagion effect on stocks. The same results are found amongst Asian nations, however, for South American nations, no statistically significant effect is found while for Europe, only contagion downgrades gave a notable effect. The reason for no statistically significant results for South America could be the result of the lack of countries with sufficient data and also the lack of rating changes for the three nations included. For Europe, the lack of an effect from downgrades could also be the result of data from only using three rating agencies.

Downgrades and upgrades from other nations are found to have no contagion effects amongst emerging markets, Europe or Asia. South America was excluded due to matrix error issues. In addition, no asymmetric effect is found; with upgrades as well as downgrades having a statistically significant effect on bond volatility.

The lack of a significant contagion effect of credit rating on bonds across countries could be the result of a lack of variability amongst government bond indices. As Larrain et al. (1997) and Reisen (1999) note for emerging markets, governments bonds are not actively traded, being mostly held by long-term institutional investors or by central banks. Most of the indices used in the study are government bond indices. In addition, Christiansen’s (2007) study notes that in stable periods, close-to-close daily returns on international stock markets tend to underestimate correlations.

Table 7: Estimation results of regressions of stock and bond market volatilities with nine agencies Eq (5)

Events		***Stock Market***								***Bond Market***							
		Emerging Markets		**South America**		**Europe**		**Asia**		**Emerging Markets**		**South America**		**Europe**		**Asia**	
Upgrade	*t*	*-0.0000000572*		-0.0000006191		-0.0000011817		0.0000004896		0.0000458097		-0.0000024459		-0.0000420818		-0.0000080490	
		(0.012)		(0.028)		(0.206)		0.064		1.837	*	(0.232)		(0.768)		(0.580)	
	t - 1	*0.0000004171*		-0.0000115598		-0.0000046995		0.0000122127		0.0000224241		-0.0000021229		-0.0000106730		-0.0000085028	
		0.093		(0.592)		(0.810)		1.597		0.860		(0.201)		(0.184)		(0.613)	
	t - 2	*-0.0000006565*		0.0000021427		0.0000036949		0.0000010826		0.0000597757	*	0.0000020873		0.0000936305		-0.0000074544	
		(0.146)		0.098		0.636		0.141		2.295		0.198		1.625		(0.537)	
Downgrade	*t*	*0.0000312641*	***	0.0000040397		0.0000044523		0.0000725093	***	0.0001179469	***	0.0000044588		0.0001672692	***	-0.0000020518	
		7.337		0.176		0.870		8.359		7.456		0.598		5.862		(0.066)	
	t - 1	*0.0000047840*		-0.0000139057		0.0000086640	*	0.0000043773		0.0000043144		0.0000095547		0.0001157396	***	0.0000014714	
		1.122		(0.607)		1.694		0.503		0.272		1.283		4.046		0.047	
	t - 2	*-0.0000044334*		0.0000046270		-0.0000000325		-0.0000030445		-0.0000586186	***	0.0000162681	**	0.0000040184		0.0000018215	
		(1.040)		0.202		(0.006)		(0.350)		(3.675)		2.185		0.140		0.059	
Upgrade Others	*t*	*-0.0000008237*		0.0000092121		-0.0000021930		-0.0000021413		-0.0000031475		0.0000004596		0.0000085252		-0.0000005522	
		(1.026)		0.609		(1.375)		(0.911)		(0.443)		0.043		0.280		(0.063)	
	t - 1	*-0.0000004976*		0.0000041199		-0.0000022209		0.0000004558		0.0000020548		-0.0000058327		0.0000240155		-0.0000019642	
		(0.618)		0.272		(1.385)		0.194		0.288		(0.533)		0.772		(0.227)	
	t - 2	*-0.0000002518*		0.0000083228		-0.0000018314		0.0000019304		-0.0000056729		-0.0000070628		0.0000131721		-0.0000005506	
		(0.312)		0.551		(1.142)		0.822		(0.796)		(0.670)		0.424		(0.063)	
Downgrade Others	*t*	0.0000005672		0.0000140640		0.0000017401		0.0000068494	**	0.0000027870		0.0000045872		0.0000026677		-0.0000027962	
		0.661		0.970		1.095		2.561		0.540		0.974		0.142		(0.156)	
	t - 1	0.0000036101	***	-0.0000046635		0.0000054833	***	0.0000190104	***	-0.0000011010		-0.0000025407		-0.0000161845		-0.0000034091	
		4.213		(0.321)		3.456		7.104903475779356		(0.213)		(0.539)		(0.866)		(0.191)	
	t - 2	0.0000007136		-0.0000124506		0.0000000512		-0.0000030883		-0.0000011760		-0.0000038317		-0.0000156601		-0.0000009436	
		0.832		(0.859)		0.032		(1.153)		(0.228)		(0.831)		(0.844)		(0.052)	
Lagged Volatility		0.9760530728	***	0.9446536033		0.9747170752	***	0.98569835	***	0.6208511734	***	0.764765835	***	0.013825792		0.089331298	***
		1853.992		438.728		1024.863		1376.437		127.625		148.775		0.013		6.291	
R^2		0.964		0.912		0.964		0.980		0.710		0.875		0.582		0.173	
Observations		168060		9753		54573		54300		25093		4897		6740		4847	
Countries		21		3		7		6		11		2		3		2	
#Upgrades		117		13		47		32		66		14		26		11	
#Downgrades		128		14		57		25		91		11		53		8	
#Upgrades (Other)		4276		26		1068		472		964		40		160		40	
#Downgrades (Other)		3834		28		1200		370		1248		40		264		28	

Note: Table 5 reports the estimation results that correspond to the regression in Eq (5). Negative t-stats are reported in parenthesis. Control variables, X, in Eq (5) include daily, monthly and annual dummies.

* Represents statistical significance at 10%.

** Represents statistical significance at 5%.

*** Represents statistical significance at 1%.

In Table 7, amongst the stock exchanges, volatility spill-over was found for emerging markets as a whole, Europe and Asia, but not for South America and as such, provides evidence for continental contagion on a regional level. North America was excluded as it did not contain enough emerging markets and Africa was also excluded because there were insufficient highly functional stock and bond markets to run the panel regression. As before, nations that exhibited a near singular matrix or singular matrix errors were excluded.

The results can be complemented by Li et al.'s (2007) findings of contagion effects of credit ratings amongst Asian stock returns. In addition, spill-over effects only resulted from downgrades, upgrades lead to no sign of contagious effects on stock volatility. This is expected as Table 4 provides no evidence that a country's own ratings upgrade will affect its own stock exchange, yet alone the stock exchange of another nation. This is contrasted with Afonso et al. (2014), who finds both downgrades and upgrades to have significant volatility spill-over effects across EU nations stocks.

Table 7 also reiterates that countries' own downgrades do in fact, have a significant effect, while upgrades again are confirmed to have no effect when nine agencies are used. The direction of these contagion effects was that downgrades lead to an increase in stock volatility in non-event nations. Afonso et al. (2014) found that upgrades lead to a decrease in volatility while downgrades lead to an increase in volatility across nations.

Downgrades are shown to have a significant effect on an own country's bond volatility, for the emerging markets as a whole, and for South America and Europe. There is however no evidence of contagious effects on the volatility of bonds for emerging markets as a whole or for any of the continents. This is contrasted with Afonso et al. (2014) who found upgrades and downgrades to have significant volatility spill-over effects among EU nations. Contrary to previous results, upgrades are found to have a significant effect on an own country's bond volatility.

5 CHAPTER 5: CONCLUSION

In summation, the results of this study in Table 1 provide evidence that as the sovereign rating of a nation declines, the historical volatility inherent in the stock market clearly increased, but there is no visual pattern for bonds. On average of the emerging markets, speculative grade nations experience approximately 2.76 times more volatility in their stock markets and 4.93 times more in their bond markets than their investment grade counterparts. The results are in line with Heinke (2006) and Jaramillo and Tejada (2011).

Table 2 shows that shocks in stock and bond return volatility exhibit persistence, and the asymmetric phenomenon where negative return shocks have more of an impact on future returns, than positive return shocks. As such, this adds to the findings of Nelson (1991) and Engle et al. (2012).

Tables 3 and 4 provide concreate evidence that supports earlier literature such as Afonso et al. (2014) in that rating downgrades have a significant impact on stock volatility, while upgrades have no such statistically significant effect. It can be concluded that the asymmetric effect of rating downgrades perpetuates from returns to the second moments of stocks, and that downgrades lead to increased stock volatility and as such, greater market uncertainty. However, for bonds, Table 3 finds no evidence of an asymmetric effect while Table 4 does. Both tables of results however, do conclude that downgrades do affect bond volatility and may even increase bond volatility.

Tables 6 and 7 provide evidence of contagion amongst emerging stock markets as a whole, and in addition, find contagion effects amongst the continents of Europe and Asia, but this effect is a result of downgrades in non-event nations with only a slight contagion effect from upgrades found in Table 6. These downgrade contagion effects lead to increased volatility of non-event nations. As for bonds, there is no evidence of contagion effects found amongst emerging markets as a whole, or any of the individual continents in Tables 6 and 7, thus conflicting with Afonso et al.'s (2014) result of significant volatility spill-over in the EU bond market. This is the most surprising result as bonds have been found to be reactive to contagion effects amongst other studies (Christiansen, 2007), but no evidence is present in Tables 6 and 7. Besides this contradictory result, all other findings were in line with expectations.

The importance of the findings, as mentioned before, are three fold. It adds to the current theoretical knowledge of sovereign credit ratings, and their impact of emerging markets, as it provides new insight into the pricing of emerging market assets.

Second, it provided valuable information to international investors and portfolio managers who wish to avoid unwanted risk. From this study, they can take the understanding that when it comes to stocks and bonds as financial instruments, downgrades are a significant risk factor to their bottom line, while upgrades are less worrisome. Arezki (2011) evidenced that during financial crises, stock markets are shown to react to rating changes in foreign countries more quickly than to rating changes in their own country. Thus, downgrades from neighbouring nations can significantly increase volatility inherent in non-event nation's stock markets, and as such, investors can anticipate greater market uncertainty resulting from rating downgrades in neighbouring nations. This is especially true for emerging markets in Europe and Asia.

Third, for policy makers a solid understanding of downgrades as a predictor of increased market uncertainty, will allow for proactive measures which can lessen the likelihood of a default or prolonged recession. Li et al. (2007) and Mora (2006) found no evidence of the pro-cyclicality of sovereign ratings amongst nations, while Kraussl (2005) found evidence of pro-cyclicality on a SMP index. This study however, reaches the same recommendation as Christopher et al. (2012) in that rating agencies need to monitor and revise ratings in a timely manner in order not to exacerbate pro-cyclical effects and avoid volatility spill-overs.

Larrain (1997) and Reinsen (1999) emphasise the ability of policy makers to smooth the business cycle and dampening crises are part of this smoothing process. Our study extends their recommendation, in that policy makers need to watch for possible volatility spill-overs from other emerging markets, especially in their regional vicinity. This needs to be interpreted with caution however, as the spill-over, while a signal for possible contagion, could have resulted from a shock in developed economies. Ismailescu and Kazemi (2010) point to the common lender and international trade as possible transmission mechanisms. However, rating changes that cause volatility in other emerging markets, regardless of origination, are signals for possible contagion amongst emerging markets.

Future research on the topic could go further in-depth by demonstrating what the basis point benefit to an individual investor would be, of factoring in rating downgrades from home nations and also by factoring in contagion effects. This could be done using a portfolio optimising mean variance approach as demonstrated in Afonso et al. (2014). In addition to the possible financial gain, it can be demonstrated how sovereign rating information can assist investors in their calculation of VAR (Value at risk). The approach would be to compare the VAR of portfolios which factor in ratings information vs those that do not, in line with Afonso et al. (2014). Furthermore, this study could be replicated with actively traded bonds such as in Larrain et al. (1997) instead of government bond indices, as the increased variation from trading might provide a more accurate measure of contagion effects.

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APPENDIX

Data source for daily stock and bond data. Included country, index and Bloomberg code

Brazil -	Ibovespa Brazil Sao Paulo Stock Exchange Index	IBOV Index
	Brazil Government Generic Bond 10 Year index	GEBR10Y
Bulgaria -	Bulgaria Stock Exchange Sofix Index	SOFIX Index
	Generic Bulgaria 10 year bond index	GTBGN10Y
China -	Shanghai Stock Exchange Composite Index	SHCOMP Index
	Generic china 10 year government bond index	GTCNY10Y
Czech Republic -	Prague Stock Exchange PX index	PX Index
	Generic Czech 10 year Government bond index	GTCZK10Y
Colombia -	Bolsa de Valores de Colombia COLCAP Index	IGBC Index
	Generic Colombia 10 year government bond index	GTCOP10Y
Croatia -	Croatia Zagreb Stock Exchange Crobex Index	CRO Index
	Generic Croatia 10 year Government Bond index	GTHRK10Y
Egypt -	Egyptian Exchange EGX30	EGX30 Index
	Egyptian 10 year treasury bonds index	EGPT10Y
Greece -	Athens Stock Exchange market Index	FTSEA Index
	Generic Greece 10 year government bond	GTGRD10Y
Hungary -	Budapest stock exchange Index	BUX Index
	Generic Hungary 10 year government bond	GTHUF10Y
India -	NIFTY Index	NIFTY
	Generic India 10 year Government Bond	GTINR10Y
Indonesia -	Jakarta stock exchange composite index	JCI
	Generic Indonesia 10 year government bond	GTIDR10Y
Israel -	Tel Aviv 25 Index	TA-25
	Current Israel 10 year government bond	CTILS10Y
Jamaica -	Jamaica Stock Exchange Market index	JMD
	Current Jamaica USD 10 Year Government Bond	GTUSDJM10Y
Lithuania -	OMX Vilnius Index	VILSE
	Current Lithuania EUR 10 Year Government Bond	CTEURLT10Y
Malaysia -	FTSE Bursa Malaysia KLCI Index (Kuala Lumpur composite Index)	FBMKLCI
	Current Malaysia 10 year Government Bond	CTMYR10Y
Mexico -	Mexican Bolsa IPC Index	MEXBOL
	Generic Mexico USD 10 Year Government bond	GTUSDMX10Y
Nigeria -	Nigerian Stock Exchange Main board index	NGSEINDX
	Generic Nigeria 10 year government bond	GTNGN10Y
Pakistan -	Karachi Stock Exchange KSE100 Index	KSE100
	Generic Pakistan 10 year Government Bond	GTPKR10Y
Panama -	Bolsa de Valores de Panama General Index	BVPSBVPS
	Generic Panama 10 year Government Bond	GTPAB10Y
Peru -	Bolsa de Valores de Lima General Sector Index	IGBVL
	Generic Peru 10 Year Government Bond	GTPEN10Y
Philippines -	Philippines stock exchange PSEi Index	PCOMP
	Generic Philippines 10 year government bond	GTPHP10Y
Poland -	Warsaw stock exchange WIG total return index	WIG
	Generic Poland 10 year Government Bond	GTPLN10Y
Romania -	Bucharest stock exchange trading index	BET
	Generic Romania 10 year Government Bond	GTRON10Y
Russia -	Russian Trading system cash Index	RTSI$

	Generic Russia 10 year government bond	GTRUB10Y
Slovakia -	Slovak Share Index	SKSM
	Generic Slovakia 10 year government Bond	GTSKK10Y
Slovenia -	Ljubljana stock exchange Slovenian Blue-Chip SBITOP Index	SBITOP
	Generic Slovenia 10 year government bond	GTSIT10Y
South Africa -	FTSE/JSE Africa All Share Index	JALSH
	Generic South Africa 10 Year Government Bond	GTZAR10Y
Thailand -	Bangkok SET Index	SET
	Generic Thailand 10 Year Government Bond	GTTHB10Y
Turkey -	Borsa Istanbul 100 Index	XU100
	Generic Turkey 10 Year Government Bond	GTTRY10Y
Ukraine -	Ukraine PFTS Index	PFTS
	Generic Ukraine 10 Year Government Bond	GTUAH10Y
Venezuela -	Caracas Stock Exchange Stock Market Index	IBVC
	Generic Venezuela 10 Year Government Bond	GTVEF10Y

Countries included in Panel regressions

Table 3 Stock Market: Croatia, Czech Republic, Egypt, Greece, Hungary, India, Israel, Jamaica, Lithuania, Malaysia, Mexico, Nigeria, Pakistan, Peru, Philippines, Poland, Russia, Slovakia, Slovenia, South Africa, Thailand, Turkey, Ukraine, Venezuela.

Table 3 Bond Market: Brazil, Greece, Jamaica, Nigeria, Philippines, Poland, Slovenia, South Africa, Ukraine, Venezuela.

Table 4 Stock Market: Colombia, Croatia, Egypt, Greece, India, Indonesia, Israel, Lithuania, Malaysia, Mexico, Nigeria, Pakistan, Peru, Philippines, Poland, Russia, Slovakia, Slovenia, South Africa, Thailand, Turkey, Ukraine, Venezuela.

Table 4 Bond Market: Bulgaria, Colombia, Czech Republic, Egypt, Hungary, India, Jamaica, Malaysia, Nigeria, Panama, Philippines, Poland, Russia, Slovakia, South Africa, Thailand, Turkey, Venezuela.

Table 5 Stock Market GJR GARCH: Brazil, Bulgaria, China, Colombia, Croatia, Egypt, Greece, Hungary, India, Israel, Jamaica, Lithuania, Malaysia, Mexico, Nigeria, Pakistan, Panama, Peru, Philippines, Poland, Russia, Slovakia, Slovenia, South Africa, Thailand, Turkey, Ukraine, Venezuela.

Table 5 Bond Market GJR GARCH: Brazil, Bulgaria, China, Colombia, Croatia, Egypt, Greece, Hungary, India, Israel, Jamaica, Malaysia, Mexico, Nigeria, Pakistan, Panama, Peru, Philippines, Poland, Russia, Slovakia, Slovenia, South Africa, Thailand, Turkey, Ukraine, Venezuela.

Table 6 Stock Market Emerging: Croatia, Czech Republic, Egypt, Greece, Hungary, India, Israel, Jamaica, Lithuania, Malaysia, Mexico, Nigeria, Pakistan, Peru, Philippines, Poland, Russia, Slovakia, Slovenia, South Africa, Thailand, Ukraine, Venezuela.

Table 6 Stock Market South America: Colombia, Peru, Venezuela.

Table 6 Stock Market Europe: Czech Republic, Greece, Hungary, Lithuania, Poland, Slovenia.

Table 6 Stock Market Asia: India, Israel, Malaysia, Pakistan, Philippines, Russia.

Table 6 Bond Market Emerging: Brazil, Greece, Jamaica, Nigeria, Philippines, Poland, Slovenia, South Africa, Ukraine, Venezuela.

Table 6 Bond Market Europe: Greece, Poland, Ukraine.

Table 6 Bond Market Asia: Pakistan, Philippines.

Table 7 Stock Market Emerging: Bulgaria, Colombia, Croatia, Greece, Hungary, India, Israel, Jamaica, Lithuania, Malaysia, Mexico, Nigeria, Pakistan, Peru, Philippines, Poland, Russia, Slovakia, Slovenia, Ukraine, Venezuela.

Table 7 Stock Market South America: Colombia, Peru, Venezuela.

Table 7 Stock Market Europe: Czech Republic, Greece, Hungary, Lithuania, Poland, Romania, Slovenia.

Table 7 Stock Market Asia: India, Israel, Malaysia, Pakistan, Philippines, Russia.

Table 7 Bond Market Emerging: Brazil, Colombia, Greece, Jamaica, Nigeria, Philippines, Poland, Slovenia, South Africa, Ukraine, Venezuela.

Table 7 Bond Market South America: Brazil, Colombia.

Table 7 Bond Market Europe: Greece, Poland, Ukraine.

Table 7 Bond Market Asia: Pakistan, Philippines.

Table 8: Augmented Dickey Fuller test results

	Stock Return			*Bond Return*		
Country	Intercept	Trend and Intercept	None	Intercept	Trend and Intercept	None
Brazil	0	0	0	0.0001	0	0.0001
Bulgaria	0.0001	0	0.0001	0.0001	0	0.0001
China	0.0001	0	0.0001	0.0001	0	0.0001
Colombia	0.0001	0	0.0001	0	0	0
Croatia	0	0	0	0	0	0
Czech Republic	0.0001	0.0001	0.0001	0	0	0
Egypt	0	0	0.0001	0	0	0
Greece	0.0001	0.0001	0.0001	0	0	0
Hungary	0.0001	0.0001	0.0001	0.0001	0	0.0001
India	0.0001	0	0.0001	0.0001	0.0001	0.0001
Indonesia	0.0001	0	0.00001	0	0	0
Israel	0.0001	0.0001	0.0001	0	0	0
Jamaica	0	0	0	0	0	0
Lithuania	0	0	0.0001	0	0	0
Malaysia	0	0	0	0.0001	0	0.0001
Mexico	0.0001	0.0001	0.0001	0.0001	0	0.0001
Nigeria	0.0001	0	0.0001	0	0	0
Pakistan	0	0	0	0.0001	0	0.0001
Panama	0.0001	0.0001	0.0001	0	0	0.0001
Peru	0	0	0	0.0001	0	0.0001
Philippines	0.0001	0	0.0001	0.0001	0.0001	0.0001
Poland	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001
Romania	0.0001	0.0001	0.0001	0	0	0
Russia	0.0001	0.0001	0.0001	0.0001	0	0.0001
Slovakia	0	0	0	0.0001	0	0.0001
Slovenia	0.0001	0	0.0001	0	0	0
South Africa	0.0001	0.0001	0.0001	0.0001	0	0.0001
Thailand	0.0001	0	0.0001	0.0001	0	0.0001
Turkey	0.0001	0.0001	0.0001	0	0	0
Ukraine	0.0001	0	0.0001	0	0	0.0001
Venezuela	0.0001	0	0.0001	0.0001	0	0.0001

Note: The values reported are P-vales for the ADF test. The test was conducted with 3 separate tests for each nation, with an intercept, with an intercept and a trend coefficient and with neither. The lags for the ADF test were set using the Schwarz Info Criterion.